CMIP6 skill at predicting interannual to multi-decadal summer monsoon precipitation variability

Article

Accepted Version

Monerie, Paul-Arthur, Robson, Jon I., Ndiaye, Cassien D., Song, Cenyao and Turner, Andrew G. (2023) CMIP6 skill at predicting interannual to multi-decadal summer monsoon precipitation variability. Environmental Research Letters. ISSN 1748-9326 doi: https://doi.org/10.1088/1748-9326/acea96 (In Press) Available at https://centaur.reading.ac.uk/112717/

To link to this article DOI: http://dx.doi.org/10.1088/1748-9326/acea96

Publisher: Institute of Physics

ENVIRONMENTAL RESEARCH
LETTERS

CMIP6 skill at predicting interannual to multi-decadal summer monsoon precipitation variability

To cite this article before publication: Paul-Arthur Monerie *et al* 2023 *Environ. Res. Lett.* in press https://doi.org/10.1088/1748-9326/acea96

CMIP6 skill at predicting interannual to multi-decadal summer monsoon precipitation variability

Paul-Arthur Monerie[1*], Jon I Robson[1], Cassien D Ndiaye[2,3], Cenyao Song[4], Andrew G Turner[1,5].

[1] National Centre for Atmospheric Science, Reading, United Kingdom
[2] LPAO-SF/Cheikh Anta Diop University, Dakar, Senegal
[3] LOCEAN/IPSL/Sorbonne University, Paris, France
[4] Previously at Department of Meteorology, University of Reading, Reading, United Kingdom
[5] Department of Meteorology, University of Reading, Reading, United Kingdom
*Author to whom any correspondence should be addressed.

Paul-Arthur Monerie; https://orcid.org/0000-0002-5304-9559. p.monerie@reading.ac.uk

Jon I Robson; https://orcid.org/0000-0002-3467-018X

Cassien D. Ndiaye; https://orcid.org/0000-0002-7091-1438

Cenyao Song

Andrew G Turner; https://orcid.org/0000-0002-0642-6876

Keywords: summer monsoon precipitation; prediction systems; skill; interannual variability; multi-decadal variability

Abstract

Monsoons affect the economy, agriculture, and human health of two thirds of the world's population. Therefore, predicting variations in monsoon precipitation is societally important. We explore the ability of climate models from the 6th phase of the Climate Model Intercomparison Project (CMIP6) to predict summer monsoon precipitation variability by using hindcasts from the Decadal Climate Prediction Project (Component A). The multi-model ensemble-mean shows significant skill at predicting summer monsoon precipitation from one year to 6-9 years ahead. However, this skill is dependent on the model, monsoon domain, and lead-time. In general, the skill of the multi-model ensemble-mean prediction is low in year 1 but increases for longer-lead times and is largely consistent with externally forced changes. The best captured region is northern Africa for the 2-5- and 6-9-year forecast lead times. In contrast, there is no significant skill using the ensemble-mean over East and South Asia and, furthermore, there is significant spread in skill among models for these domains. By sub-sampling the ensemble we show that the difference in skill between models is tied to the simulation of the externally forced response over East and South Asia, with models with a more skilful forced response capable of better predictions. A further contribution is from skilful prediction of Pacific Ocean temperatures for the South Asian summer monsoon at longer lead-times. Therefore, these results indicate that predictions of the East and South Asian monsoons could be significantly improved.

1. Introduction

Two thirds of the world's population lives in areas where there is a monsoon in summer (Wang & Ding, 2006). Monsoon precipitation variability has effects on economies, agriculture, and human health, among other sectors. Therefore, predicting the future evolution of monsoon precipitation is important, for adaptation strategies (*e.g.*, infrastructure planning).

Individual predictions systems have shown skill at predicting monsoon precipitation on a large range of time scales (Dunstone et al. 2020; Monerie et al. 2021). Regionally, some skill has been found over East and southern Africa (Beraki et al., 2013; Monerie et al., 2018; Walker et al., 2019), South America (Jones et al., 2012), Australia (King et al., 2020), India (Chevuturi et al., 2021; Johnson et al., 2017) and southern China (Lu et al., 2017) at a seasonal time scale. On longer time scales, prediction systems have exhibited substantial skill at predicting decadal variations in Sahel precipitation (Gaetani & Mohino, 2013; Martin & Thorncroft, 2014; Mohino et al., 2016; Ndiaye et al., 2022; Otero et al., 2016; Sheen et al., 2017).

There are multiple sources of skill for predicting summer monsoon precipitation. The role of sea surface temperatures (SSTs), among other slowly varying lower boundary conditions, in predicting monsoon precipitation variations, was theorised by Charney and Shukla (1981). On seasonal time scales, it was shown that the El Niño Southern Oscillation (ENSO) is key for providing skill at predicting precipitation over the tropics (Dunstone et al., 2020; Shukla & Paolino, 1983; Sohn et al., 2019; Wang et al., 2018). On decadal time scales, the North Atlantic and Indian Ocean SSTs also yield a certain amount of predictability for monsoon precipitation (Mohino et al., 2016; Wang et al., 2018), due to the high prediction skill of prediction systems for Atlantic and Indian Ocean sea surface temperature (García-Serrano et al., 2015; Guemas et al., 2013) and to the effects of these oceanic basins on monsoon precipitation.

Anthropogenic forcing is a source of prediction skill for global mean surface air temperature (Boer et al., 2016) and SST (*e.g.*, Guemas et al. 2013) and has known effects on summer monsoon precipitation worldwide (Marvel et al. 2020; Monerie et al. 2022).

Previous studies have quantified skill at predicting monsoon precipitation on multi-year time scales with a small number of climate models and ensemble members (*e.g.*, Bellucci et al. 2015). However, prediction skill values increases with ensemble size (Smith et al., 2019) and we therefore use the large ensemble of the Decadal Climate Prediction Project (DCPP; Boer et al. 2016), reducing unpredictable noise, and providing a better estimate of prediction skill. The large ensemble facilitates understanding of the causes of differences between prediction systems at predicting monsoon precipitation, including structural differences between prediction systems. No robust evaluation across a range of models, monsoon domains and timescales has been provided so far. We thus provide, for the first time, a quantification of the ability of CMIP6 prediction systems at predicting interannual to decadal summer monsoon precipitation variability in a global monsoon framework. We expect skill at predicting summer monsoon precipitation to be model dependent (as shown by Delgado-Torres et al. (2022) for the surface air temperature), area-dependent and lead-time dependent.

We address the following questions:

- Are CMIP6 initialized prediction systems skilful at predicting summer monsoon precipitation on interannual-to-decadal time scales?
- How model dependent is the skill at predicting summer monsoon precipitation?
- Can we identify the sources of skill?

The paper is organised as follows: section 2 describes the simulations and the methodologies used. In section 3 we quantify skill at prediction monsoon precipitation for the multi model mean and for each individual prediction system. Sources of skill are shown in section 4. We discuss results in section 5 and section 6 concludes the main findings of the study.

2. Methods and data

2.1 Data

We use hindcasts of 9 climate models from DCPP Component A (Boer et al., 2016) (DCPPA hereafter). These climate predictions are initialised from observationally constrained datasets every year from 1960 to 2019 and 5 to 10 ensemble members are used depending on the climate model (Table 1). We assume 5 to 10 ensemble members to be large enough to allow considerably increased prediction skill of monsoon precipitation (Jain et al., 2019; Monerie et al., 2021). DCPPA simulations are initialised in November each year and last for 5 to 10 years after initialisation and are forced with historical external forcing.

We assess the impact of initialisation by comparing DCPPA simulations to the uninitialized CMIP6 historical simulations (Eyring et al., 2016; Table S1), using the same climate models. These historical simulations begin in 1850 and last for ~150 years (1850-2014) and use the same external forcings as the DCPPA simulations. Prior to analysis, observations and simulations are first interpolated onto a common 1° horizontal grid.

We assess skill at predicting precipitation using the data of the Climate Research Unit (CRU; Harris et al. 2014), available from 1901 to present. Skill at predicting surface air temperature is quantified using the NCEP reanalysis (Kanamitsu et al., 2002), which is given on a 2.5° x 2.5° horizontal resolution and from 1948 to present.

2.2 Method

2.2.1 Assessing skill

Prediction skill is estimated using the Anomaly Correlation Coefficient (ACC) metric, computed between observed and simulated time series. We assess skill at three lead times. The one-year lead time allows determination of skill at predicting interannual variability in summer monsoon precipitation and is months 14-17 (8-11) for the southern (northern) hemisphere in DJFM (JJAS). Years 2-5 and years 6-9 are 4 years averaged between year 2 to 5 and 6 to 9, respectively, and documents predictability of the summer monsoon precipitation on longer time scales. Prediction skill is assessed over the period 1960-2020.

We estimate the significance of the ACC by randomly resampling time series of the ensemble means. We use a 5-year block bootstrap to conserve low-frequency variability in precipitation and temperature using 5000 permutations in a Monte Carlo framework. The ACC values are judged significant at the $p<0.05$ level if the correlations are stronger than 97.5% of the randomly obtained correlation values, using a two-sided test.

We acknowledge that ACC scores are sensitive to the existence of linear trends (*e.g.*, in precipitation, Figure S1). However, we note that removing a linear trend can artificially improve skill (Figure S2). Therefore, we document the skill at predicting the total summer monsoon variability (internal variability + variability induced by the externally forced response).

2.2.2 Drift correction

DCPPA simulations are initialised from observationally constrained datasets, but then drift away to reach their own model's climatology. The drift can result in fast and large changes in temperature and precipitation (Hermanson et al., 2018). Hence, we remove the lead-time-dependent drift following the World Climate Research Programme recommendations (ICPO, 2011) (see Drift Correction in the Supplementary Material) prior to displaying simulated time series. Note that removing the drift does not impact skill as defined by the ACC.

2.2.3 Persistence

The *n*-year persistence is computed based on the observed values in the *n* years prior to the start date. We computed a 1-year and a 4-year persistence.

2.2.4 Defining ensembles

We define ensembles to explore the spread in model skill and to understand sources of prediction skill for summer monsoon precipitation.

2.2.4.1 Ensemble mean (ENSM and HIST)

We assess the ability of DCPPA simulations to predict monsoon precipitation by defining the ensemble mean across models and ensemble members, hereafter called ENSM, as:

$$\bar{P}(j) = \frac{1}{m}\sum_{i=1}^{m} P_i^j,$$

with P precipitation of all m ensemble members i and for each start date j, and $\bar{P}$ precipitation averaged across all ensemble members and start date. m is the total number of ensemble members across all models.

HIST is defined in the same way as ENSM but using the uninitialized simulations. Uninitialized ensemble members simulate internal climate variability, but ensemble members would not be expected to be in-phase and the ensemble mean is an estimate of the forced response to external drivers (*e.g.*, Deser et al. 2012). Therefore, the comparison of ENSM and HIST allows for an exploration of the importance of initialisation for the prediction skill.

2.2.4.2 Best Model (BEST)

The prediction system that performs best is selected, according to the ACC values, with the BEST ensemble consisting of only one individual model, for each monsoon domain and each lead-time.

2.2.4.3 A subset of models (SUBSET and WORST SUBSET)

The SUBSET approach follows the ENSM approach, computing the ensemble mean with only the three prediction systems that have the highest ACC values over a given monsoon domain and for a given lead time. The composition of the SUBSET ensemble is, thus, monsoon domain and lead time dependent.

The WORST SUBSET is defined in the same way as SUBSET but selecting the three prediction models that have the lowest ACC values. We expect a comparison of SUBSET against WORST SUBSET and ENSM to provide information on sources of prediction skill. Finally, the effect of initialisation is here estimated by comparing SUBSET with HIST SUBSET, which is composed of the same models as SUBSET but using historical uninitialized simulations only.

2.2 Monsoon domains

Monsoon domains are defined where the difference between May to September (MJJAS) and November to March (NDJFM) precipitation exceeds 2.5 mm.d^{-1} (Wang et al., 2011) in observations (GPCC; Schneider et al. 2014). We only consider precipitation that falls within the tropical latitudes [30°S-30°N] and over land. Monsoon domains are shown in Figure 1 and are named NAM (Northern America), NAF (Northern Africa), SAS (South Asia), EAS (East Asia), SAM (Southern America), SAF (Southern Africa) and AUS (Australia), following the literature (e.g., Kitoh et al. 2013). We assess skill at predicting summer monsoon precipitation, in JJAS for the NAM, NAF, SAS and EAS monsoon domains and in DJFM for the SAM, SAF and AUS monsoon domains. In addition, we averaged monsoon precipitation of all domains in the northern (NHM) and southern (SHM) Hemispheres.

2.3 The Interdecadal Pacific Oscillation

We define the Interdecadal Pacific Oscillation (IPO) as the difference between the central-eastern Pacific [150°E-150°W; 10°S-10°N] and the tropical central-eastern Pacific [170°W-90°W; 25°N-45°N] after Huang et al. (2020), using surface air temperature. According to Huang et al. (2020), this index gives similar results that the tripole index of Henley et al. (2015).

3. DCPPA prediction skill

3.1 Quantifying DCPPA ensemble-mean prediction skill

We assess prediction skill of ENSM for summer monsoon precipitation at each grid point, and when averaged over each monsoon domain.

We find significant skill in predicting summer monsoon precipitation in ENSM, but the skill appears to increase with lead time. Figure 1a shows that skill at predicting precipitation at the 1-year forecast lead time is relatively low over much of the globe, although there are regions with statistically significant prediction skill. For example, over the tropics, prediction skill is significant over northern South America, Argentina, and the western Sahel. Nevertheless, relative to the 1-year predictions, we find an increase in skill for the 2-5 and 6-9 forecast lead times. This increase in skill stands out over the Sahel, western India and Southeast Asia, and northern South America (Figure 1b and Figure 1c).

Figure 2 shows the skill at predicting summer monsoon precipitation when averaged over all monsoon domains. At the 1-year forecast lead time, ENSM is skilful at predicting NAM and AUS precipitation, as well as the hemisphere-wide quantities (NHM and SHM) (Figure 2a). However, there is no significant skill over the NAF, SAS, EAS, SAM and SAF monsoon domains. For the 2-5 and 6-9-year forecast lead times, skill remains statistically significant for NHM, SHM, and NAM precipitation (Figure 2b and Figure 2c) and increases substantially for NAF and SAM precipitation. In contrast, ENSM does not show significant skill for the SAS, EAS and SAF monsoon domains for any lead-time. Results show higher skill for ENSM than for the CMIP5 decadal prediction systems (Bellucci et al. 2015).

We assess the sources of model skill at predicting summer monsoon precipitation variability compared with persistence forecasts and with uninitialized simulations. Figure 2 shows that ENSM prediction skill generally exceeds persistence, implying that the skill does not only depend on the inertia of the climate system. We note, however, that persistence is more skilful than ENSM for the 1-year and 2-5-year forecast lead times for NAF summer monsoon precipitation (Figure 2a and Figure 2b). The effect of initialisation (defined as the difference between initialised and uninitialized hindcasts) only emerges for a limited number of monsoon domains, especially at the longer lead times (*e.g.*, 6-9 years), indicating that changes in external forcing are an important source of prediction skill on these time scales.

3.2 Understanding the range of prediction skill

So far, we have only explored the multi-model mean skill. But modelling systems will likely exhibit different levels of skill. Figure 2 also shows the range of skill for each model in the DCPPA ensemble and there is a significant diversity of model skill for all lead times (purple vertical lines). There is a consensus for some monsoon domains and lead-times, with all models exhibiting positive skill (*e.g.*, NAM summer monsoon precipitation for the 1-year forecast lead-time and NAF summer monsoon precipitation for the 2-5 and 6-9 forecast lead-times). However, there is more diversity in prediction skill for the SAS and EAS domains, with individual models performing much better or lesser than ENSM (Figure 2b and Figure 2c), as also shown with seasonal hindcasts (Jain et al., 2019; Mishra et al., 2018). Skill scores for each model and monsoon domain are shown in Figure S3 and Figure S4.

4. Sources of prediction skill

We explore the source of skill by selecting models according to their prediction skill. As expected, the BEST and SUBSET ensembles generally show improved skill relative to ENSM for all forecast lead time (Figure 3).

ACC value is around tripled in SUBSET (ACC=0.61) compared to ENSM (ACC=0.18) for EAS summer monsoon precipitation and the 2–5-year forecast lead time (Figure 3b and Table S2). ACC values is approximately quadrupled in SUBSET (ACC=0.40) relative to ENSM (ACC=0.09) for SAS summer monsoon precipitation and for the 6–9-year forecast lead time (Figure 3c and Table S3). This is a consequence of the large diversity in prediction skill over South and East Asia, with prediction systems exhibiting either high or low skill. Thus, skilful predictions can be obtained in the regions that ENSM is not skilful. We used another observational dataset (GPCC) and show that results are robust across observations (not shown).

4.1 Source of prediction skill for EAS summer monsoon precipitation

We focus on prediction of EAS summer monsoon precipitation for the 2–5-year forecast lead time, for which the SUBSET-ENSM difference in skill is the largest. The improved skill in SUBSET, relative to ENSM, is largely due to the multi-decadal variation in EAS summer monsoon precipitation. After applying a 7-year running mean to the 2-5-year forecasts we find the ACC is 0.70 in SUBSET but only 0.14 in ENSM. This is further confirmed using a 21-year running mean to only capture the slow variation of the EAS summer monsoon precipitation (Figure S5). In contrast, the difference in skill between SUBSET (ACC=0.18) and ENSM (ACC=0.07) is low when considering higher frequency variability (defined as the residual relative to the 7-year running mean). Figure 4a shows the smoothed time series in EAS summer monsoon precipitation. Although there is significant skill in SUBSET, both ENSM and SUBSET ensemble underestimate the observed variability. The difference between SUBSET and ENSM ensembles is that there is a long-lasting drying trend in ENSM while SUBSET simulates a small decrease in precipitation from 1960 to the 1980s and an increase in precipitation afterwards, hence better following the observation (Figure 4a). In contrast, the WORST SUBSET shows a strong drying trend. Therefore, the difference in trends appears to be key to understand the differences in monsoon precipitation skill.

There is a large effect of the externally forced response on the multi-annual variation in EAS summer monsoon precipitation, as evidenced by the high correlation coefficient between the uninitialized and initialised simulations (r^*=0.94 between ENSM and HIST; Figure 4a).

Hence, we hypothesise that the range in skill of the DCPPA ensemble to be due to the differences in the response to external forcing. This is assessed by comparing maps of SUBSET-WORST SUBSET difference in skill (Figure 5a) to the HIST SUBSET-HIST WORST SUBSET difference in skill (Figure 5b). As the skill of uninitialized simulations is due to the response to the external forcing, the strong similarity between Figure 5a and Figure 5b confirms a strong role of the simulation of the externally forced response on the spread in prediction skill over EAS. These results have a strong societal importance because the increase in skill is the highest over eastern China, a heavily populated region where precipitation variability is high (Figure 5a).

4.2 Sources of prediction skill for SAS summer monsoon precipitation

We focus on prediction of SAS summer monsoon precipitation for the 6–9-year forecast lead time, for which the SUBSET-ENSM difference in skill is the greatest. As for EAS summer monsoon precipitation, the externally forced response has strong effects on the long-term variation in simulated SAS summer monsoon, as shown by the high correlation coefficient between uninitialized and initialised simulations (r*=0.98 between ENSM and HIST; Figure 4b). The spread in SAS summer monsoon prediction skill is also associated with the ability of prediction systems to simulate the multi-decadal variation in SAS summer monsoon precipitation. This is evidenced by the absence of pre-1990 drying in WORST SUBSET, while SUBSET shows a multi-decadal variation in SAS summer monsoon precipitation, in better agreement with the observations (Figure 4b).

An effect of the response to external forcing on the spread of South Asian summer monsoon prediction skill is confirmed by the similarity between patterns of difference in prediction skill (SUBSET-WORST SUBSET; Figure 5c, and HIST SUBSET- HIST WORST SUBSET; Figure 5d). However, the response to externally forced response does not fully explain the SUBSET-WORST SUBSET difference in skill. We thus also expect other drivers of South Asian summer monsoon precipitation variability to contribute to the spread in SAS summer monsoon precipitation skill.

The multi-decadal variability in South Asian precipitation has been linked to the interdecadal variability of the Pacific Ocean (IPO) (Huang et al., 2020; Zhang et al., 2018). We show a strong relationship between skill at predicting the IPO and that of the SAS summer monsoon precipitation at the 6–9-year forecast lead time (Figure 6b; r=0.88). The spread at predicting the IPO thus also contribute to the spread at prediction the SAS summer monsoon precipitation. We performed the same analysis with the uninitialized simulations and show that the result of Figure 6b is due to initialisation (r=0.01 with the uninitialized simulations), and thus to the simulation of internal climate variability and to the correction of an incorrect forced response.

5 Discussion

Although we show improved skill over EAS and SAS summer monsoon precipitation in SUBSET, which we attribute to the impact of external forcing and to the simulation of the IPO, the exact mechanisms that explain the higher skill are unclear. For example, we explored mechanisms focusing on known drivers of the monsoon circulation, such as the large-scale gradients in surface air temperature and of surface air temperature over the oceans. However, differences in skill at predicting surface air temperature between the SUBSET and ENSM ensembles are low (Figure S6 and Figure S7). Further work could focus on understanding differences in atmospheric circulation, and regional changes between SUBSET and ENSM. We also acknowledge that different estimations of the internal components of the IPO could lead to different conclusions and future work could be devoted to understanding what leads to better prediction skill of the IPO and its role for predicting summer monsoon precipitation at multi-annual forecast lead times. In addition, the results are expected to be sensitive to the estimate of the IPO (*e.g.*, (Henley et al., 2015; Parker et al., 2007) and to the use of different observations/reanalysis. However, we show that skill at predicting South Asian summer monsoon precipitation is sensitive to the skill at predicting the Pacific Ocean SSTs for the 6-9-year forecast lead-time.

We explored further the role of the IPO indices on summer monsoon prediction skill, correcting IPO indices and effects on summer monsoon precipitation, using observations. We show that an improved prediction skill for the IPO leads to a better prediction skill for the SAS summer monsoon precipitation (Figure S8 and text in the supplementary material). Better predicting the IPO can allow improved prediction skill over South Asia. In addition to the IPO, we found a moderate relationship between skill at predicting North Atlantic temperature and SAS summer monsoon precipitation (r=0.35) for the 6-9- year forecast lead-time. In contrast, prediction skill of the IPO has no effects on prediction skill for EAS summer monsoon precipitation (Figure 6a; r=-0.18) and we found no relationship between prediction of the North Atlantic, Indian Ocean, and equatorial Pacific Ocean temperature on prediction skill of EAS summer monsoon precipitation skill (not shown) for the 2-5- year forecast lead-time.

We acknowledge here that we do not suggest the full skill of the prediction systems to arise only due to the externally forced response. Instead, we suggest that differences in skill in initialised predictions are partly due to differences in the simulation of the externally forced response. These differences in skill could be due to model biases. However, we found no relationships between biases in seasonal mean precipitation (or variability) and prediction skill, when using monsoon domain averages (not shown). Yet, further work might identify the importance of model biases for prediction skill. A focus could be given to the biases in simulation of the mean state tropical SSTs (*e.g.*, Turner et al. 2005). We also highlight that an increased number of models could allow increasing robustness of the results.

6 Conclusions

We quantify the ability of CMIP6 initialized decadal prediction systems (Boer et al. 2016) to predict summer monsoon precipitation in a global monsoon framework and focus on three forecast lead times (1 year, 2-5 years, and 6-9 years). Overall, skill is low for the forecast 1-year lead time but increases for the 2-5- and 6-9-year horizons. Furthermore, the skill is model dependent, monsoon-domain dependent and lead-time dependent.

We explore sources of skill for predicting summer monsoon precipitation. In particular, the impact of initialisation is rather small when focusing on the 2-5 and 6-9 forecast lead times. Therefore, the results highlight the importance of the externally forced response for providing skill at predicting summer monsoon precipitation. By selecting models, based on their prediction skill, we suggest that differences in simulating the externally forced response between models explains a large proportion of the diversity skill of the CMIP6 model ensemble, over South and East Asia.

Nevertheless, differences in skill at predicting the Interdecadal Pacific Oscillation (IPO) also contributes to differences in skill between models for predictions of the South Asian summer monsoon precipitation at the 6-9-year forecast lead time. We show that initialisation and improved prediction of the Pacific SSTs is important for prediction of South Asian summer monsoon precipitation, but it is unclear if this is due to improved prediction of internal variability, a correction of an incorrect forced response or mean state. Besides, we acknowledge that skill at predicting the IPO can be a manifestation of an effect of the externally forced response on temperature over the Pacific Ocean. Therefore, improving our understanding of the differences between how models simulate the effects of external forcing and of the Interdecadal Pacific Oscillation on South and East Asian summer monsoon precipitation could be an important avenue for improving prediction skill on a multi-annual time scale The mechanism (*e.g.*, anomalies in atmospheric circulation, in temperature gradients) that explains model skill diversity remains unclear. Further work is needed, focusing on, for instance, the atmosphere dynamics or model biases.

We do not argue here that selecting models based on their prediction skill should be used for predicting the future evolution of the East and South Asian summer monsoon precipitation up to ten years ahead. A reason for that is that prediction skill depends on the period used as reference (Figure S9) and the ensembles might thus not provide the best prediction for the coming decade.

Acknowledgements.

JR was funded by NERC via the ACSIS (NE/N018001/1) and CANARI (NE/W004984/1) programs, and the WISHBONE (NE/T013516/1) project. CDN was supported by PDI/MSC (Programme Doctoral International: Modélisation des Systèmes Complexes), the scholarship of SCAC (Service de Coopération et d'Action Culturelle), the ERASUMUS+ programme through action KA107, and the Laboratoire Mixte International ECLAIRS2 (IRD), the UCM XVII call for cooperation and sustainable development. AGT was funded via the National Centre for Atmospheric Science through the NERC National Capability International Programme Award (NE/X006263/1).

We acknowledge the World Climate Research Programme's Working Group on Coupled Modelling, which is responsible for CMIP, and we thank the climate modelling groups for producing and making available their model output. For CMIP the U.S. Department of Energy's Program for Climate Model Diagnosis and Intercomparison provides coordinating support and led development of software infrastructure in partnership with the Global Organization for Earth System Science Portals. We also thank the two anonymous reviewers for their comments and suggestions.

Data availability statement

CMIP6 GCM output is available at https://esgf-node.llnl.gov/search/cmip6/. DOIs/URLs for the historical simulations are https://doi.org/10.22033/ESGF/CMIP6.3610, https://doi.org/10.22033/ESGF/CMIP6.3825, https://doi.org/10.22033/ESGF/CMIP6.4700, https://doi.org/10.22033/ESGF/CMIP6.6112, https://doi.org/ 10.22033/ESGF/CMIP6.5195, https://doi.org/10.22033/ESGF/CMIP6.5603, https://doi.org/10.22033/ESGF/CMIP6.6594, https://doi.org/10.22033/ESGF/CMIP6.6842, https://doi.org/10.22033/ESGF/CMIP6.10894, respectively for CanESM5, CMCC-CM2-SR5, EcEARTH3, HadGEM3-GC31-MM, IPSL-CM6A-LR, MIROC6, MPI-ESM1-2-HR, MRI-ESM2-0 and NorCPM1. DOIs/URL for the hindcasts are https://doi.org/10.22033/ESGF/CMIP6.3557, https://www.wdc-climate.de/ui/entry?acronym=C6_4368435, https://doi.org/10.22033/ESGF/CMIP6.4553, https://doi.org/10.22033/ESGF/CMIP6.5892, https://doi.org/10.22033/ESGF/CMIP6.5137, https://doi.org/10.22033/ESGF/CMIP6.890, https://doi.org/10.22033/ESGF/CMIP6.768, https://doi.org/10.22033/ESGF/CMIP6.630 and https://doi.org/10.22033/ESGF/CMIP6.10865, respectively for CanESM5, CMCC-CM2-SR5, EcEARTH3, HadGEM3-GC31-MM, IPSL-CM6A-LR, MIROC6, MPI-ESM1-2-HR, MRI-ESM2-0 and NorCPM1. NCEP temperature data are provided by the NOAA/OAR/ESRL PSL, Boulder, Colorado, USA, from their website at https://downloads.psl.noaa.gov/Datasets/ncep.reanalysis/Monthlies/pressure/. CRU Precipitation is provided by the Climate Research Unit, from the website at https://crudata.uea.ac.uk/cru/data/hrg/cru_ts_4.03/cruts.1905011326.v4.03/pre/.

Models	Institutions	No. of ensemble members	Length of the integrations (years)	Horizontal resolution (lat x lon)	References
CanESM5	Canadian Center for Climate Modeling and Analysis, Canada	10	10	64 x 128	(Swart et al., 2019)
CMCC-CM2-SR5	Fondazione Centro Euro-Mediterraneo sui Cambiamenti Climatici. Italy	6	10	192 x 288	(Cherchi et al., 2019)
EcEarth3	EC-Earth-Consortium	10	10	256 x 512	(Wyser et al., 2020)
HadGEM3-GC31-MM	Met Office Hadley Centre, United Kingdom	10	10	324 x 432	(Kuhlbrodt et al., 2018)
IPSL-CM6A-LR	Institut Pierre Simon Laplace, France	10	10	144 x 143	(Boucher et al., 2020)
MIROC6	Japanese modeling community, Japan	10	10	128 x 256	(Tatebe et al., 2019)
MPI-ESM1-2-HR	Deutsches Klimarechenzentrum, Germany	5	10	192 x 384	(Mauritsen et al., 2019)
MRI-ESM2-0	Meteorological Research Institute, Japan	10	5	160 x 320	(Yukimoto et al., 2019)
NorCPM1	NorESM Climate modeling Consortium	10	10	96 x 144	(Bethke et al., 2021)

Table 1: List of DCPPA prediction systems and number of simulations used in the study

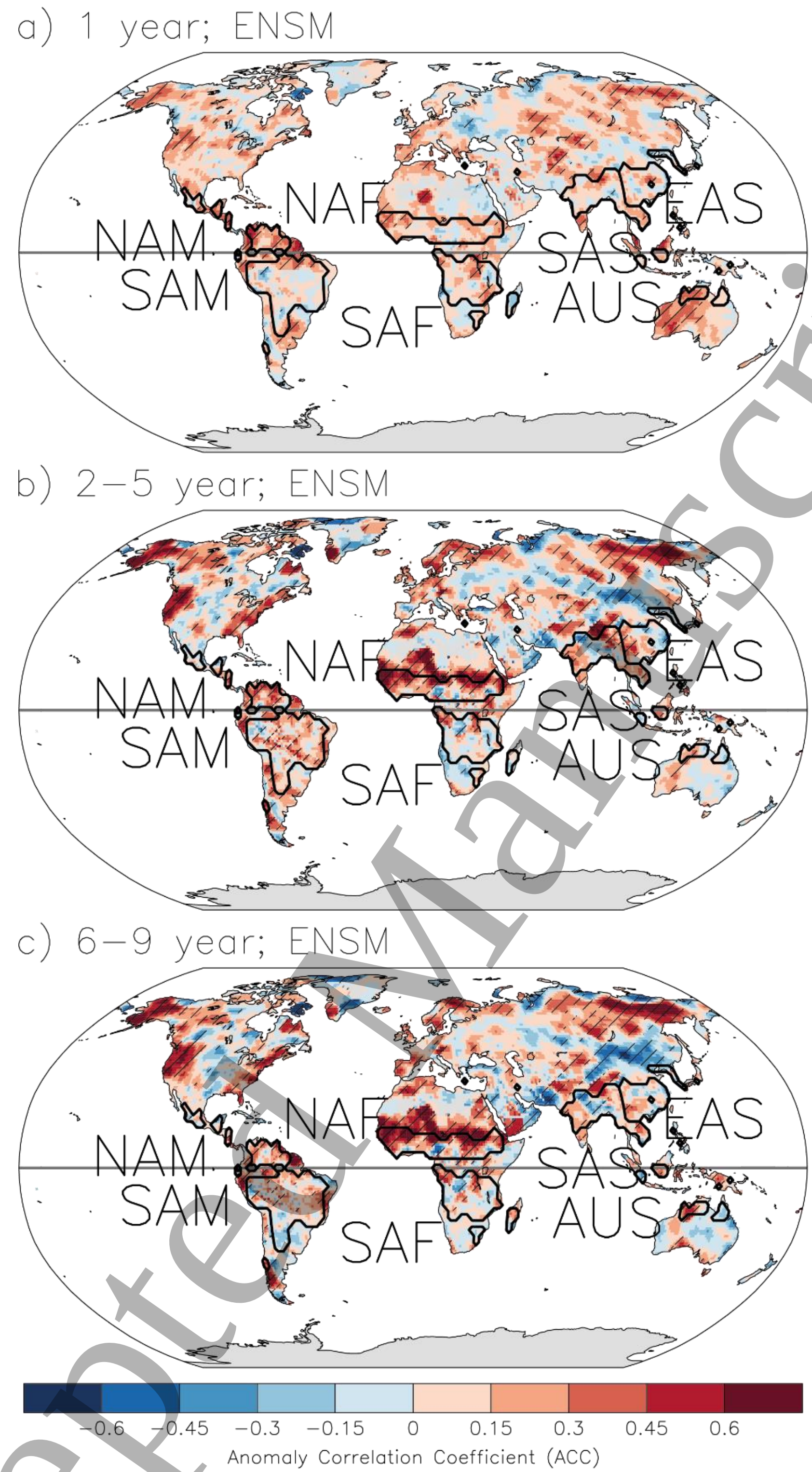

Figure 1. Anomaly correlation coefficient skill score for predictions of precipitation in ENSM at the (a) 1, (b) 2-5 and (c) 6-9-year forecast lead times, relative to CRU. ACC values are shown for JJAS (DJFM) in the northern (southern) hemisphere. Stippling indicates that ACC is significantly different to zero according to a Monte-Carlo procedure with 5000 permutations and a 95% confidence level. Black contours show the monsoon domains.

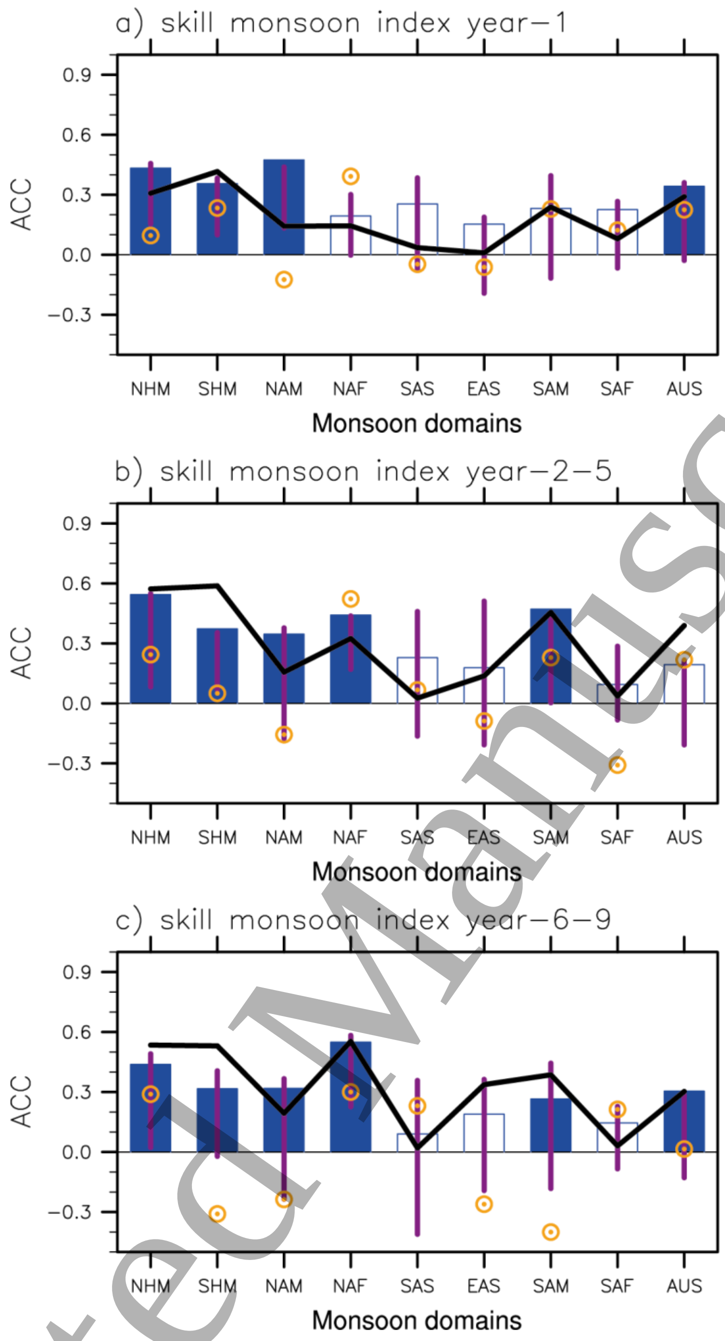

Figure 2: Anomaly correlation coefficient skill score for predictions of summer monsoon precipitation averaged over each monsoon domain and for the northern hemisphere (NHM) and the southern hemisphere (SHM). Results are given for ENSM (bars), uninitialized simulations (black line), and persistence (orange circles), and for the (a) 1-year, (b) 2-5 year, and (c) 6-9-year forecast lead times. The magenta vertical line shows the range in DCPPA prediction skill, defined between the lowest and highest skill and from each prediction system. A solid blue bar indicates that ACC is significantly different to zero according to a Monte-Carlo procedure with 5000 permutations and a 95% confidence level.

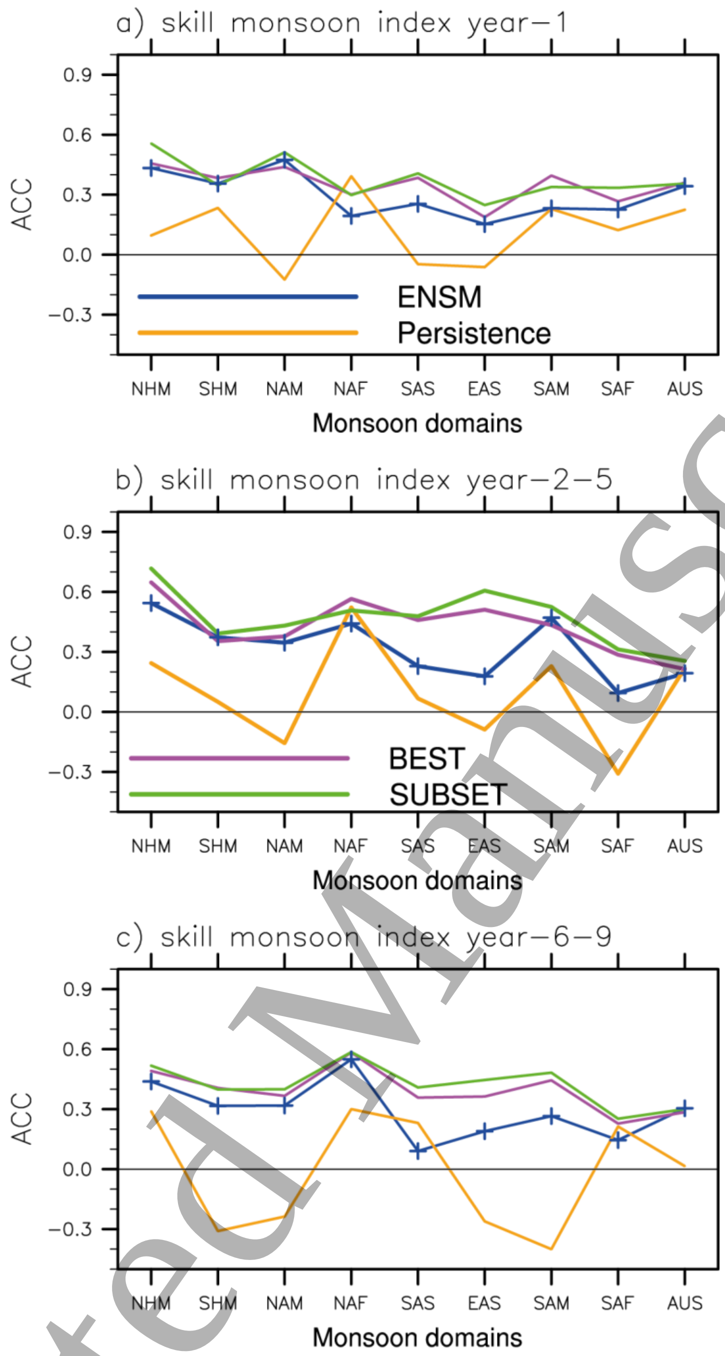

Figure 3: Anomaly correlation coefficient skill score for predictions of summer monsoon precipitation averaged over the northern hemisphere (NHM), the southern hemisphere (SHM) and each monsoon domain. Results are given for ENSM (dark blue), persistence (orange), BEST (magenta), and SUBSET (light green). Results are given for the (a) 1-year, (b) 2-5 year, and (c) 6-9-year forecast lead times.

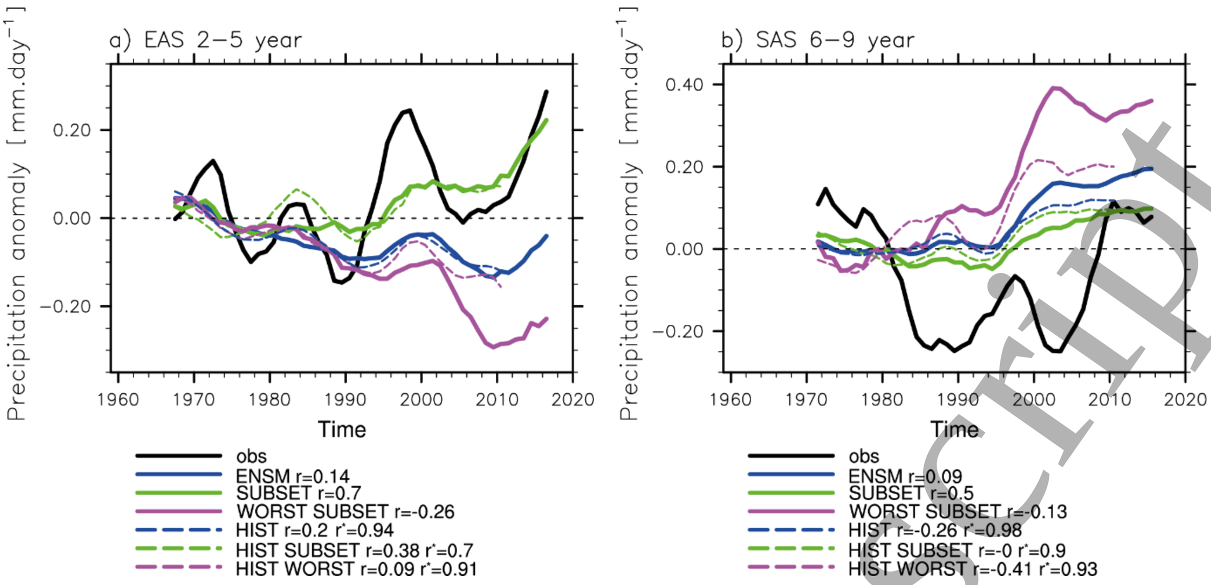

Figure 4: Precipitation anomalies in (a) EAS and (b) SAS summer monsoons, for the 2-5- and 6-9-year forecast lead times, respectively. Observations (CRU) are shown in black, ENSM in blue, SUBSET in green, WORST SUBSET in magenta, and HIST with discontinuous black line. Anomalies are computed relative to the 1961-1981 period. The high frequency variability is removed using a 7-year running average after computing the 2-5 and 6-9 averages. The *r* number indicates the ACC value, computed between each ensemble and observations, the *r** number indicates the correlation coefficient between initialized and uninitialized simulations.

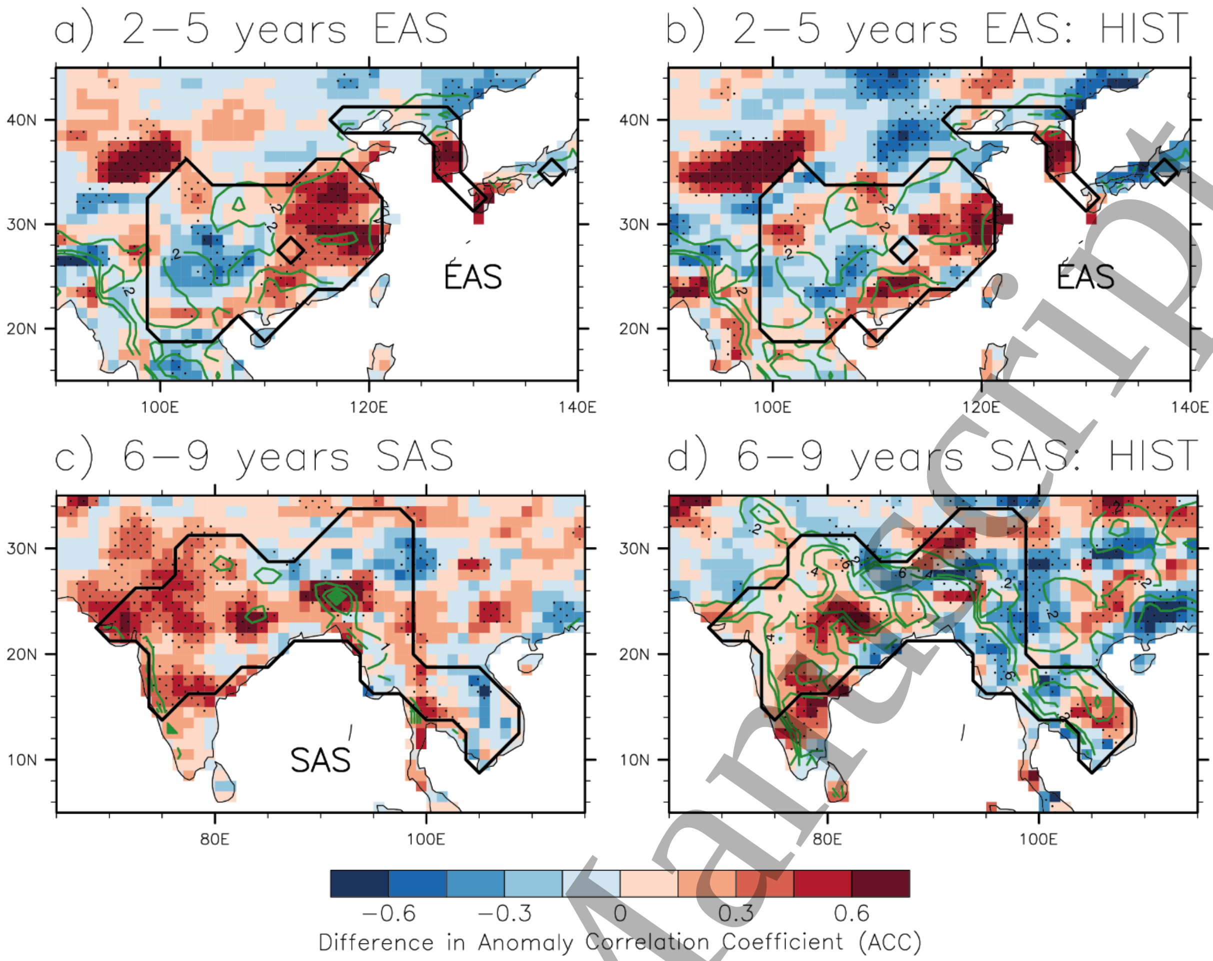

Figure 5: SUBSET minus WORST SUBSET difference in anomaly correlation coefficient skill score for predictions of precipitation over (a) East Asia for the 2-5-year forecast lead time, (c) South Asia for the 6-9-year forecast lead time. Skill at predicting precipitation is computed in comparison to CRU. Green contours indicate the precipitation variance, in $mm^2.d^{-2}$. (b) and (d), as in (a) and (c) but for the HIST SUBSET-HIST WORST SUBSET difference in anomaly correlation coefficient skill score for precipitation. Stippling indicates that the difference in ACC is significantly different to zero according to a Monte-Carlo procedure, resampling both BEST and ENSM and computing difference in ACC values. We use 5000 permutations and a 95% confidence level. The same number of ensemble members are used for the ensembles of initialised and uninitialized simulations (19 ensemble members for HIST SUBSET and 26 ensemble members for WORST SUBSET for EAS summer monsoon precipitation; 30 ensemble members for HIST SUBSET and 15 ensemble members for WORST SUBSET and for the SAS summer monsoon precipitation.)

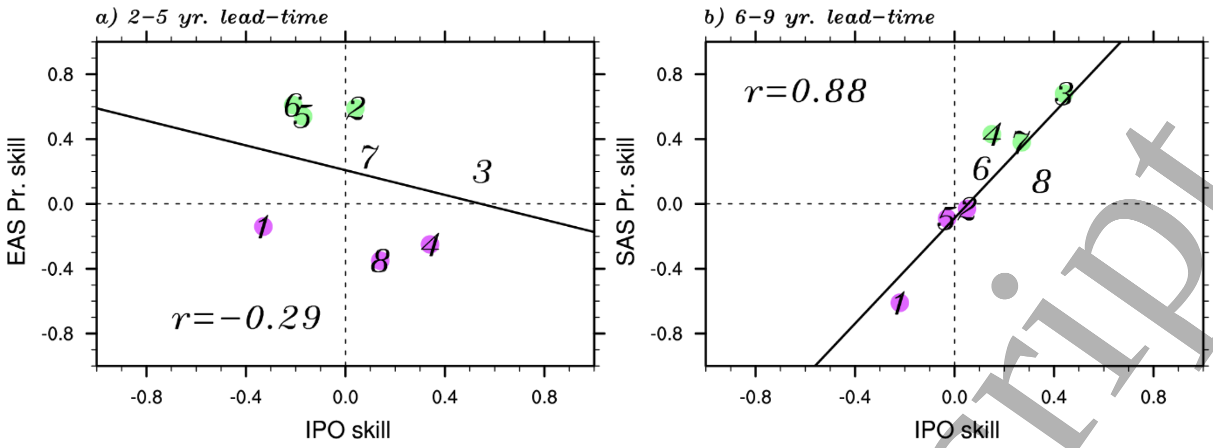

Figure 6: Anomaly correlation coefficient skill score for predictions of IPO index and (a) EAS and (b) SAS summer monsoon precipitation for each prediction system (1-CMCC-CM2-SR5; 2-HadGEM3-GC31-MM; 3-IPSL-CM6A-LR; 4-MIROC6; 5-MPI-ESM1-2-HR; 6-CanESM5; 7-EcEarth3; 8-NorCPM1) and the 2-5- and 6-9-year forecast lead times, respectively. A 7-year running mean was applied to both precipitation and IPO time series before to compute anomaly correlation coefficients. SUBSET (WORST SUBSET) models are shown with a green (magenta) circle.

References

Bellucci, A., Haarsma, R., Gualdi, S., Athanasiadis, P. J., Caian, M., Cassou, C., Fernandez, E., Germe, A., Jungclaus, J., Kröger, J., Matei, D., Müller, W., Pohlmann, H., Salas y Melia, D., Sanchez, E., Smith, D., Terray, L., Wyser, K., & Yang, S. (2015). An assessment of a multi-model ensemble of decadal climate predictions. *Climate Dynamics*, *44*(9–10), 2787–2806. https://doi.org/10.1007/s00382-014-2164-y

Beraki, A. F., DeWitt, D. G., Landman, W. A., & Olivier, C. (2013). Dynamical Seasonal Climate Prediction Using an Ocean–Atmosphere Coupled Climate Model Developed in Partnership between South Africa and the IRI. *Journal of Climate*, *27*(4), 1719–1741. https://doi.org/10.1175/JCLI-D-13-00275.1

Bethke, I., Wang, Y., Counillon, F., Keenlyside, N., Kimmritz, M., Fransner, F., Samuelsen, A., Langehaug, H., Svendsen, L., Chiu, P.-G., Passos, L., Bentsen, M., Guo, C., Gupta, A., Tjiputra, J., Kirkevåg, A., Olivié, D., Seland, Ø., Solsvik Vågane, J., … Eldevik, T. (2021). NorCPM1 and its contribution to CMIP6 DCPP. *Geoscientific Model Development*, *14*(11), 7073–7116. https://doi.org/10.5194/gmd-14-7073-2021

Boer, G. J., Smith, D. M., Cassou, C., Doblas-Reyes, F., Danabasoglu, G., Kirtman, B., Kushnir, Y., Kimoto, M., Meehl, G. A., Msadek, R., Mueller, W. A., Taylor, K. E., Zwiers, F., Rixen, M., Ruprich-Robert, Y., & Eade, R. (2016). The Decadal Climate Prediction Project (DCPP) contribution to CMIP6. *Geoscientific Model Development*, *9*(10), 3751–3777. https://doi.org/10.5194/gmd-9-3751-2016

Boucher, O., Servonnat, J., Albright, A. L., Aumont, O., Balkanski, Y., Bastrikov, V., Bekki, S., Bonnet, R., Bony, S., Bopp, L., Braconnot, P., Brockmann, P., Cadule, P., Caubel, A., Cheruy, F., Codron, F., Cozic, A., Cugnet, D., D'Andrea, F., … Vuichard, N. (2020). Presentation and Evaluation of the IPSL-CM6A-LR Climate Model. *Journal of Advances in Modeling Earth Systems*, *12*(7), e2019MS002010. https://doi.org/10.1029/2019MS002010

Charney, J. G., & Shukla, J. (1981). *Predictability of monsoons. Monsoon Dynamics, J. Lighthill and RP Pearce, Eds*. Cambridge University Press.

Cherchi, A., Fogli, P. G., Lovato, T., Peano, D., Iovino, D., Gualdi, S., Masina, S., Scoccimarro, E., Materia, S., Bellucci, A., & Navarra, A. (2019). Global Mean Climate and Main Patterns of Variability in the CMCC-CM2 Coupled Model. *Journal of Advances in Modeling Earth Systems*, *11*(1), 185–209. https://doi.org/https://doi.org/10.1029/2018MS001369

Chevuturi, A., Turner, A. G., Johnson, S., Weisheimer, A., Shonk, J. K. P., Stockdale, T. N., & Senan, R. (2021). Forecast skill of the Indian monsoon and its onset in the ECMWF seasonal forecasting system 5 (SEAS5). *Climate Dynamics*, *56*(9), 2941–2957. https://doi.org/10.1007/s00382-020-05624-5

Delgado-Torres, C., Donat, M. G., Gonzalez-Reviriego, N., Caron, L.-P., Athanasiadis, P. J., Bretonnière, P.-A., Dunstone, N. J., Ho, A.-C., Nicoli, D., Pankatz, K., Paxian, A., Pérez-Zanón, N., Cabré, M. S., Solaraju-Murali, B., Soret, A., & Doblas-Reyes, F. J. (2022). Multi-Model Forecast Quality Assessment of CMIP6 Decadal Predictions. *Journal of Climate*, *35*(13), 4363–4382. https://doi.org/10.1175/JCLI-D-21-0811.1

Deser, C., Phillips, A., Bourdette, V., & Teng, H. (2012). Uncertainty in climate change projections: the role of internal variability. *Climate Dynamics*, *38*(3), 527–546. https://doi.org/10.1007/s00382-010-0977-x

Dunstone, N., Smith, D., Yeager, S., Danabasoglu, G., Monerie, P.-A., Hermanson, L., Eade, R., Ineson, S., Robson, J. I., & Scaife, A. A. (2020). Skilful interannual climate prediction from two large initialised model ensembles. *Environmental Research Letters*.

Eyring, V., Bony, S., Meehl, G. A., Senior, C. A., Stevens, B., Stouffer, R. J., & Taylor, K. E. (2016). Overview of the Coupled Model Intercomparison Project Phase 6 (CMIP6) experimental design and organization. *Geoscientific Model Development*, *9*(5), 1937–1958. https://doi.org/10.5194/gmd-9-1937-2016

Gaetani, M., & Mohino, E. (2013). Decadal Prediction of the Sahelian Precipitation in CMIP5 Simulations. *Journal of Climate*, *26*(19), 7708–7719. https://doi.org/10.1175/JCLI-D-12-00635.1

García-Serrano, J., Guemas, V., & Doblas-Reyes, F. J. (2015). Added-value from initialization in predictions of Atlantic multi-decadal variability. *Climate Dynamics*, *44*(9–10), 2539–2555. https://doi.org/10.1007/s00382-014-2370-7

Guemas, V., Corti, S., García-Serrano, J., Doblas-Reyes, F. J., Balmaseda, M., Magnusson, L., Guemas, V., Corti, S., García-Serrano, J., Doblas-Reyes, F. J., Balmaseda, M., & Magnusson, L. (2013). The Indian Ocean: The Region of Highest Skill Worldwide in Decadal Climate Prediction*. *Journal of Climate*, *26*(3), 726–739. https://doi.org/10.1175/JCLI-D-12-00049.1

Harris, I., Jones, P. D., Osborn, T. J., & Lister, D. H. (2014). Updated high-resolution grids of monthly climatic observations – the CRU TS3.10 Dataset. *International Journal of Climatology*, *34*(3), 623–642. https://doi.org/10.1002/joc.3711

Henley, B. J., Gergis, J., Karoly, D. J., Power, S., Kennedy, J., & Folland, C. K. (2015). A Tripole Index for the Interdecadal Pacific Oscillation. *Climate Dynamics*, *45*(11), 3077–3090. https://doi.org/10.1007/s00382-015-2525-1

Hermanson, L., Ren, H.-L., Vellinga, M., Dunstone, N. D., Hyder, P., Ineson, S., Scaife, A. A., Smith, D. M., Thompson, V., Tian, B., & Williams, K. D. (2018). Different types of drifts in two seasonal forecast systems and their dependence on ENSO. *Climate Dynamics*, *51*(4), 1411–1426. https://doi.org/10.1007/s00382-017-3962-9

Huang, X., Zhou, T., Turner, A., Dai, A., Chen, X., Clark, R., Jiang, J., Man, W., Murphy, J., Rostron, J., Wu, B., Zhang, L., Zhang, W., & Zou, L. (2020). The Recent Decline and Recovery of Indian Summer Monsoon Rainfall: Relative Roles of External Forcing and Internal Variability. *Journal of Climate*, *33*(12), 5035–5060. https://doi.org/10.1175/JCLI-D-19-0833.1

ICPO. (2011). Data and bias correction for decadal climate predictions. *International CLIVAR Project Office Publication Series*, *150:5*((Available online at http://www.wcrp-climate.org/decadal/references/DCPP_Bias_Correction.pdf)).

Jain, S., Scaife, A. A., & Mitra, A. K. (2019). Skill of Indian summer monsoon rainfall prediction in multiple seasonal prediction systems. *Climate Dynamics*, *52*(9), 5291–5301. https://doi.org/10.1007/s00382-018-4449-z

Johnson, S. J., Turner, A., Woolnough, S., Martin, G., & MacLachlan, C. (2017). An assessment of Indian monsoon seasonal forecasts and mechanisms underlying monsoon interannual variability in the Met Office GloSea5-GC2 system. *Climate Dynamics*, *48*(5), 1447–1465. https://doi.org/10.1007/s00382-016-3151-2

Jones, C., Carvalho, L. M. V, & Liebmann, B. (2012). Forecast Skill of the South American Monsoon System. *Journal of Climate*, *25*(6), 1883–1889. https://doi.org/10.1175/JCLI-D-11-00586.1

Kanamitsu, M., Ebisuzaki, W., Woollen, J., Yang, S.-K., Hnilo, J. J., Fiorino, M., Potter, G. L., Kanamitsu, M., Ebisuzaki, W., Woollen, J., Yang, S.-K., Hnilo, J. J., Fiorino, M., & Potter, G. L. (2002). NCEP–DOE AMIP-II Reanalysis (R-2). *Bulletin of the American Meteorological Society*, *83*(11), 1631–1643. https://doi.org/10.1175/BAMS-83-11-1631

King, A. D., Hudson, D., Lim, E.-P., Marshall, A. G., Hendon, H. H., Lane, T. P., & Alves, O. (2020). Sub-seasonal to seasonal prediction of rainfall extremes in Australia. *Quarterly Journal of the Royal Meteorological Society*, *146*(730), 2228–2249. https://doi.org/https://doi.org/10.1002/qj.3789

Kitoh, A., Endo, H., Krishna Kumar, K., Cavalcanti, I. F. A., Goswami, P., & Zhou, T. (2013). Monsoons in a changing world: A regional perspective in a global context. *Journal of Geophysical Research: Atmospheres*, *118*(8), 3053–3065. https://doi.org/10.1002/jgrd.50258

Kuhlbrodt, T., Jones, C. G., Sellar, A., Storkey, D., Blockley, E., Stringer, M., Hill, R., Graham, T., Ridley, J., Blaker, A., Calvert, D., Copsey, D., Ellis, R., Hewitt, H., Hyder, P., Ineson, S., Mulcahy, J., Siahaan, A., & Walton, J. (2018). The Low-Resolution Version of HadGEM3 GC3.1: Development and Evaluation for Global Climate. *Journal of Advances in Modeling Earth Systems*, *10*(11), 2865–2888. https://doi.org/10.1029/2018MS001370

Lu, B., Scaife, A. A., Dunstone, N., Smith, D., Ren, H.-L., Liu, Y., & Eade, R. (2017). Skillful seasonal predictions of winter precipitation over southern China. *Environmental Research Letters*, *12*(7), 74021. https://doi.org/10.1088/1748-9326/aa739a

Martin, E. R., & Thorncroft, C. (2014). Sahel rainfall in multimodel CMIP5 decadal hindcasts. *Geophysical Research Letters*, *41*(6), 2169–2175. https://doi.org/10.1002/2014GL059338

Marvel, K., Biasutti, M., & Bonfils, C. (2020). Fingerprints of external forcing agents on Sahel rainfall: aerosols, greenhouse gases, and model-observation discrepancies. *Environmental Research Letters*, *15*(8), 084023. http://iopscience.iop.org/10.1088/1748-9326/ab858e

Mauritsen, T., Bader, J., Becker, T., Behrens, J., Bittner, M., Brokopf, R., Brovkin, V., Claussen, M., Crueger, T., Esch, M., Fast, I., Fiedler, S., Fläschner, D., Gayler, V., Giorgetta, M., Goll, D. S., Haak, H., Hagemann, S., Hedemann, C., … Roeckner, E. (2019). Developments in the MPI-M Earth System Model version 1.2 (MPI-ESM1.2) and Its Response to Increasing CO2. *Journal of Advances in Modeling Earth Systems*, *11*(4), 998–1038. https://doi.org/https://doi.org/10.1029/2018MS001400

Mishra, S. K., Sahany, S., Salunke, P., Kang, I.-S., & Jain, S. (2018). Fidelity of CMIP5 multi-model mean in assessing Indian monsoon simulations. *Npj Climate and Atmospheric Science*, *1*(1), 39. https://doi.org/10.1038/s41612-018-0049-1

Mohino, E., Keenlyside, N., & Pohlmann, H. (2016). Decadal prediction of Sahel rainfall: where does the skill (or lack thereof) come from? *Climate Dynamics*, *47*(11), 3593–3612. https://doi.org/10.1007/s00382-016-3416-9

Monerie, P.-A., Robson, J., Dong, B., Dieppois, B., Pohl, B., & Dunstone, N. (2018). Predicting the seasonal evolution of southern African summer precipitation in the DePreSys3 prediction system. *Climate Dynamics*. https://doi.org/10.1007/s00382-018-4526-3

Monerie, P.-A., Robson, J. I., Dunstone, N. J., & Turner, A. G. (2021). Skilful seasonal predictions of Global Monsoon summer precipitation with DePreSys3. *Environmental Research Letters*. http://iopscience.iop.org/article/10.1088/1748-9326/ac2a65

Monerie, P.-A., Wilcox, L. J., & Turner, A. G. (2022). Effects of anthropogenic aerosol and greenhouse gas emissions on Northern Hemisphere monsoon precipitation: mechanisms and uncertainty. *Journal of Climate*, 1–66. https://doi.org/10.1175/JCLI-D-21-0412.1

Ndiaye, C. D., Mohino, E., Mignot, J., & Sall, S. M. (2022). On the detection of externally-forced decadal modulations of the Sahel rainfall over the whole 20th century in the CMIP6 ensemble. *Journal of Climate*, 1–51. https://doi.org/10.1175/JCLI-D-21-0585.1

Otero, N., Mohino, E., & Gaetani, M. (2016). Decadal prediction of Sahel rainfall using dynamics-based indices. *Climate Dynamics*, *47*(11), 3415–3431. https://doi.org/10.1007/s00382-015-2738-3

Parker, D., Folland, C., Scaife, A., Knight, J., Colman, A., Baines, P., & Dong, B. (2007). Decadal to multidecadal variability and the climate change background. *Journal of Geophysical Research: Atmospheres*, *112*(D18). https://doi.org/https://doi.org/10.1029/2007JD008411

Schneider, U., Becker, A., Finger, P., Meyer-Christoffer, A., Ziese, M., & Rudolf, B. (2014). GPCC's new land surface precipitation climatology based on quality-controlled in situ data and its role in quantifying the global water cycle. *Theoretical and Applied Climatology*, *115*(1–2), 15–40. https://doi.org/10.1007/s00704-013-0860-x

Sheen, K. L., Smith, D. M., Dunstone, N. J., Eade, R., Rowell, D. P., & Vellinga, M. (2017). *Skilful prediction of Sahel summer rainfall on inter-annual and multi-year timescales*. *8*, 14966. http://dx.doi.org/10.1038/ncomms14966

Shukla, J., & Paolino, D. A. (1983). The Southern Oscillation and Long-Range Forecasting of the Summer Monsoon Rainfall over India. *Monthly Weather Review*, *111*(9), 1830–1837. https://doi.org/10.1175/1520-0493(1983)111<1830:TSOALR>2.0.CO;2

Smith, D. M., Eade, R., Scaife, A. A., Caron, L.-P., Danabasoglu, G., DelSole, T. M., Delworth, T., Doblas-Reyes, F. J., Dunstone, N. J., Hermanson, L., Kharin, V., Kimoto, M., Merryfield, W. J., Mochizuki, T., Müller, W. A., Pohlmann, H., Yeager, S., & Yang, X. (2019). Robust skill of decadal climate predictions. *Npj Climate and Atmospheric Science*, *2*(1), 13. https://doi.org/10.1038/s41612-019-0071-y

Sohn, S.-J., Tam, C.-Y., & Kug, J.-S. (2019). How does ENSO diversity limit the skill of tropical Pacific precipitation forecasts in dynamical seasonal predictions? *Climate Dynamics*, *53*(9), 5815–5831. https://doi.org/10.1007/s00382-019-04901-2

Swart, N. C., Cole, J. N. S., Kharin, V. V, Lazare, M., Scinocca, J. F., Gillett, N. P., Anstey, J., Arora, V., Christian, J. R., Hanna, S., Jiao, Y., Lee, W. G., Majaess, F., Saenko, O. A., Seiler, C., Seinen, C., Shao, A., Sigmond, M., Solheim, L., … Winter, B. (2019). The Canadian Earth System Model version 5 (CanESM5.0.3). *Geoscientific Model Development*, *12*(11), 4823–4873. https://doi.org/10.5194/gmd-12-4823-2019

Tatebe, H., Ogura, T., Nitta, T., Komuro, Y., Ogochi, K., Takemura, T., Sudo, K., Sekiguchi, M., Abe, M., Saito, F., Chikira, M., Watanabe, S., Mori, M., Hirota, N., Kawatani, Y., Mochizuki, T., Yoshimura, K., Takata, K., O'ishi, R., … Kimoto, M. (2019). Description and basic evaluation of simulated mean state, internal variability, and climate sensitivity in MIROC6. *Geoscientific Model Development*, *12*(7), 2727–2765. https://doi.org/10.5194/gmd-12-2727-2019

Turner, A. G., Inness, P. M., & Slingo, J. M. (2005). The role of the basic state in the ENSO–monsoon relationship and implications for predictability. *Quarterly Journal of the Royal Meteorological Society*, *131*(607), 781–804. https://doi.org/https://doi.org/10.1256/qj.04.70

Walker, D. P., Birch, C. E., Marsham, J. H., Scaife, A. A., Graham, R. J., & Segele, Z. T. (2019). Skill of dynamical and GHACOF consensus seasonal forecasts of East African rainfall. *Climate Dynamics*, *53*(7), 4911–4935. https://doi.org/10.1007/s00382-019-04835-9

Wang, B., & Ding, Q. (2006). Changes in global monsoon precipitation over the past 56 years. *Geophysical Research Letters*, *33*(6). https://doi.org/https://doi.org/10.1029/2005GL025347

Wang, B., Kim, H.-J., Kikuchi, K., & Kitoh, A. (2011). Diagnostic metrics for evaluation of annual and diurnal cycles. *Climate Dynamics*, *37*(5), 941–955. https://doi.org/10.1007/s00382-010-0877-0

Wang, B., Li, J., Cane, M. A., Liu, J., Webster, P. J., Xiang, B., Kim, H.-M., Cao, J., & Ha, K.-J. (2018).

Toward Predicting Changes in the Land Monsoon Rainfall a Decade in Advance. *Journal of Climate*, *31*(7), 2699–2714. https://doi.org/10.1175/JCLI-D-17-0521.1

Wyser, K., van Noije, T., Yang, S., von Hardenberg, J., O'Donnell, D., & Döscher, R. (2020). On the increased climate sensitivity in the EC-Earth model from CMIP5 to CMIP6. *Geoscientific Model Development*, *13*(8), 3465–3474. https://doi.org/10.5194/gmd-13-3465-2020

Yukimoto, S., Kawai, H., Koshiro, T., Oshima, N., Yoshida, K., Urakawa, S., Tsujino, H., Deushi, M., Tanaka, T., Hosaka, M., Yabu, S., Yoshimura, H., Shindo, E., Mizuta, R., Obata, A., Adachi, Y., & Ishii, M. (2019). The Meteorological Research Institute Earth System Model Version 2.0, MRI-ESM2.0: Description and Basic Evaluation of the Physical Component. *Journal of the Meteorological Society of Japan. Ser. II*, *97*(5), 931–965. https://doi.org/10.2151/jmsj.2019-051

Zhang, Z., Sun, X., & Yang, X.-Q. (2018). Understanding the interdecadal variability of East Asian summer monsoon precipitation: Joint influence of three oceanic signals. *Journal of Climate*. https://doi.org/10.1175/JCLI-D-17-0657.1